Positional Learning with Noise*

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Abstract

We propose (and test experimentally) a model of observational learning in which players hold social preferences. To this aim, we design an experiment -based on a classic parlor game known as the Chinos Game- in which we vary (by way of an exogenous iid stochastic process) the probability of getting the prize in the event of a correct guess. By this design, we are able to estimate more efficiently players' sensitivity to difference in payoffs (and how this sensitivity affects information decoding process along the sequence). We also condition our estimates upon additional information on subjects' socio-demographics, risk attitudes and cognitive reflection by way of a questionnaire we collect at the end of each session.

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1 Introduction

There are many economic contexts -such as financial markets daily routine, or the choice of firms on technological adoptions under uncertain market conditions- in which information is obtained *privately* and transmitted *sequentially*. Economists are naturally interested in the effects of this sequentiality on (equilibrium) behavior, especially in the extent with which sequentiality may impede the attainment of an efficient outcome in which all information is correctly embodied in equilibrium. Theorists, most notably Banerjee [5] and Bickchandani *et al.* [6], have shown that sequentiality of information transmission may yield inefficiency, as players undervalue their private information, thus yielding what have been labeled as *informational cascades.* Experimentalists, beginning with Anderson and Holt [3] and Allsop and Hey [1], have confirmed empirically that such information cascades do indeed occur in the lab.

The original theoretical literature we just mentioned posits a strategic environment in which players receive a stochastic private signal about the "true" state of nature. Subsequently, in a fixed sequence exogenously given, they have to guess the true state of nature, conditional on their private information and the observation of the guesses of all preceding players. In this guessing game, players do not compete with each other, since they are all rewarded with a fixed prize in case of a correct guess. In this respect, the literature has always treated the above situation as the ideal setting to analyze information transmission abstracting from strategic considerations (which are, instead, prominent, in sequential environments of a different nature, such as signaling games).

Along these lines, Feri *et al.* [13] design an experiment based on the classic parlor game known as the *Chinos' Game.* In this game, players start by hiding in their hands a certain number of marbles. Then, in some pre-specified order, each player has to guess the *total* number of marbles in the hands of every player. When doing so, a player is informed of her own number and the guesses produced by all others who preceded her.

Figure 1 reports a 2-player version of the Chinos Game, when the maximum number of marbles in the hands of each player is 1. While in the original game this number is chosen by each player, Figure 1 (by analogy with the experimental protocol) simplifies matters, leaving this decision in the hands of Nature, where the (iid) probability of holding a marble is commonly known to be $p > \frac{1}{2}$.

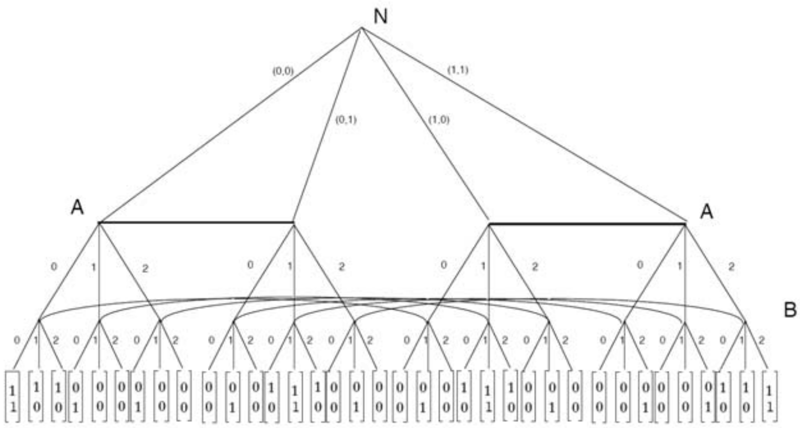

Fig. 1. The Chinos Game (2-player version)

In the game of Figure 1, all players who guess correctly win a fixed prize. Thus, the game has clear analogies with the models of positional learning we just referred to.[1] In this respect, Feri *et al.*'s [13] find systematic deviations from profit maximizing behavior, which they rationalize with a simple model of *error cascade*s, by which *the higher the probability of a deviation from optimal behavior (i.e. an error) on behalf of first movers, the higher the probability of a mistake in late-movers' behavior.*

Figure 2 provides a robustness check of Feri *et al.*'s [13] conjecture using our own experimental evidence. Figure 2 tracks, for each player position and experimental matching group, the evolution across rounds of the relative frequency of times in which subjects choose their profit maximizing guess, assuming that players' beliefs (i.e., a system of probabilities of a positive signal conditional on predecessors' guesses) are obtained by "counting" the number of time a given signal was associated with a given guess in the past (details in the Appendix).

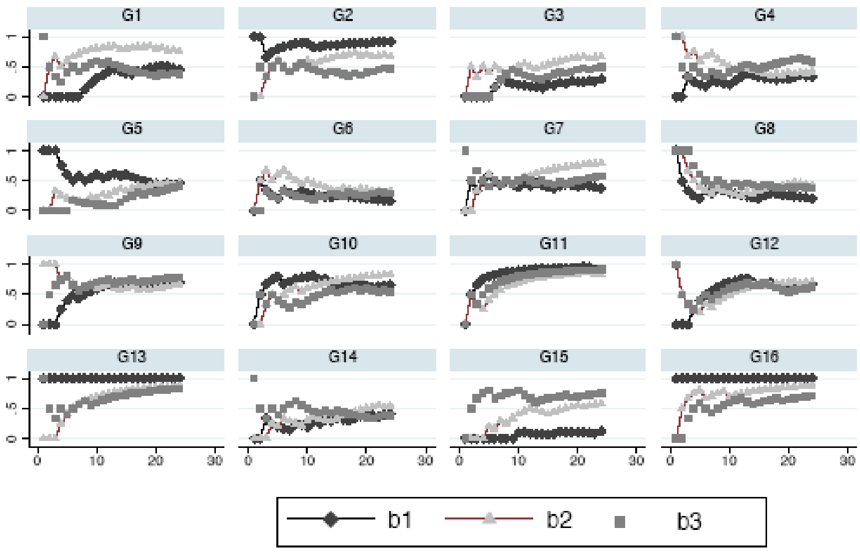

Fig. 2. Error cascades I: relative frequencies of best responses

It may be worthwhile to notice that, by maximizing their winning probability, players perfectly reveal their private signal to later movers (see (1) below). In this respect, Figure 2 shows that player 1's learning path seems to crucially affect the likelihood of the other group members to select their payoff maximizing action. In other words, the extent to which Player 1 delivers a "clean" message of her private information seems to crucially affect the likelihood of her successors to maximize profits. In Feri *et al.*'s [13], this behavioral anomaly is framed in the context of McKelvey and Palfrey's [21] Quantal Response Equilibrium (QRE henceforth). This approach postulates that *a)* players behave optimally subject to an error (with full support) and *b)* the probability of playing suboptimally is decreasing the payoff loss. Again, their analysis still maintains that players do not have strategic motives, in that they aim to maximize the probability of winning the prize (and, by doing so, they should perfectly reveal -up to an error- their private signal).

[1] See also [8], [9].

Assume, instead, that players are also moved by relative comparisons. This is very reasonable to assume in the context of positional learning, where first-movers play with a clear information handicap, and by playing "optimally" give later movers a better chance to win. To see why, look at Figure 1 and consider the situation of Anna whose highest expected payoff -which is attained by adding 1 (given $p > \frac{1}{2}$) to her signal, see (1) below- is equal to p. However, by doing so, she perfectly reveals her signal to Beppe, giving him the chance to win the prize for sure. If Anna were moved by *envy* -due to her disadvantageous position in the sequence- she may be willing to shade (at least, partially) her signal, with the aim of reducing Beppe's probability of winning, even if this implies a reduction of her own winning probability, too.

The aim of this paper is to look at the Chinos Game -here to be interpreted as a stereotypical example of positional learning environment- allowing for the possibility that *subjects (although not necessarily all of them) deviate from profit maximizing behavior moved by distributional concerns.* In this respect, this paper sits squarely in the growing experimental literature which shows that, in a wide variety of situations, people exhibit *social* (i.e. interdependent) preferences.[2] This novel theoretical spin in the analysis of positional learning motivates an experimental design in which we modify the original protocol by introducing an endogenous random shock which reduces the probability of getting the prize in the event of a correct guess of only one player in the sequence (we call her the *Selected Player*, SP), whose identity changes from one round to the next. By this design, we are able to estimate more efficiently subjects' distributional concerns (and how these concerns affect information decoding along the sequence). We also condition our estimates on additional information on subjects' demographics, risk attitudes and cognitive reflection we collect by way of a questionnaire.

The remainder of this paper is arranged as follows. In Section 2 we review the relevant literature. Theory is what we develop next, by setting up a formal account of the experimental environment (Section 3.1), together with the development of a simple theoretical model (Section 3.2) in which we show that, when relative comparisons affect players' preferences, information shading may be justified as rational (equilibrium) response.

This theoretical conjecture is then brought to its empirical validation by way the design of a specific modification of the Chinos Game, whose experimental conditions are described in detail in Section 4. Section 5 summarizes our experimental findings. Here we see that subjects' average behavior is better approximated (and best, for some of our experimental group) by a structural model which encompasses -together with noise, unavoidable in the analysis of any experimental environment- the existence of distributional motives. We also see that subjects' socio-demographics are capable of explaining a significant amount of *between-subject* heterogeneity. Specifically, we find that *a)* less risk averse and more cognitive responsive subjects show greater ability to pursue their individual objectives in the game, while *b)* women exhibit more altruistic behavior than men, in that are less inclined to deviate from full revelation to rational shading. Section 6 concludes, followed by an Appendix containing a more detailed account of Feri *et al.*'s [13] model of error cascades, additional statistical evidence, the experimental instructions and the questionnaire.

[2]This experimental evidence is well summarized in the excellent surveys of Fehr-Schmidt [12] and Sobel [22].

2 Literature survey

In this section we review two strands of literature we consider relevant to our project. Section 2.1 reports some experimental evidence on signaling games. As we mention in the introduction, once we introduce social preferences, we give players a rational motive to lie about their signal while, in the standard treatment of positional learning, they have not. The second strand refers to the role of incentive effects in the lab. This is relevant to our purpose, since our only modification to the original Chinos game protocol is exactly to introduce an exogenous shock by which the expected payoff of one player in the group is arbitrarily reduced. While the literature we survey is only focused in the analysis of *direct* incentive effects, we are also interested in *indirect* effects, i.e. the loss of trust on the other players' behalf, of the SP's message.

2.1 Deception in Signaling Games

The experimental literature on signaling games mainly deals with the so-called Sender-Receiver Game-form, by which one player (the *sender*) sends a message about her type (which she is the only one who knows), while the other player (the Receiver), once he has received the message, has to choose an action. Players' monetary payoffs only depends on the Sender's type and the Receiver's action. The main finding of this literature is that deception (i.e. senders lying about their types) is often used but, contrary to equilibrium prediction, it is often believed. This is how Sopher and Zapater [23] explain this behavioral anomaly: "*In a game with two types, even if the players know that type 1 will always send the message 'I am type 1,' they act as if they failed to understand that any other message must come from type 2*" (p. 5).

Forsythe *et al.* [15] frame the signaling game as a market for product quality. Sellers know the quality of their good (their type); buyers know only the distribution of qualities. In their cheap talk treatment, at no cost, sellers can announce a range of quality, which (they claim) includes the quality of their good. Buyers then decide whether or not to buy and at what price. Thus, in this treatment of the experiment, sellers can deceive buyers about their good's quality, and many do (186 fraudulent claims out of a total 660 claims). Equilibrium analysis predicts that buyers will not be deceived, but in the experiment they are. In another antifraud condition, sellers are constrained to include their product's true quality in the quality range they quote to buyers. Here, deception is ruled out, yet buyers still sometimes overpay for the good as "*buyers are not always sufficiently skeptical of their [seller's] statements*". In particular, the authors conclude that "*Buyers are frequently taken in by the seller's overoptimistic statements and bid too much for the asset*".[3] Finally, Gneezy [17] interprets the evidence of Sender-Receiver games by appealing to social preferences. He argues that subjects care not only about how much they gain from lying, but also how much the other side loses. While subjects are mostly sensitive to their gain when deciding to lie, this unselfish motive diminishes as the induced payoff difference grows.

2.2 Incentive effects in experiments

[3] See also Sopher and Zapater [23].

Broadly speaking, we can say that economists generally assume that experimental subjects work harder, more persistently, and more effectively if they can earn more money for better performance. By, contrast, psychologists generally believe that intrinsic motivation may produce focussed effort even in the absence of financial rewards. Hence, for economists higher payoffs lead to higher performance, while for psychologists what matters is intrinsic motivation . There is a vast literature on this topic and we report here a subset of this literature that we consider most relevant to this paper. Camerer and Hogarth [7] review 74 experiments with "no", "low" or "high" financial incentives. They found that the modal result is that there is no effect on mean performance, though the variance reduces in the presence of higher incentives. Gneezy and Rustichini [18] find that the effect of monetary compensation on performance is not monotonic: in a treatment where monetary compensation was offered, higher compensation generally led to higher performance. However offering money does not always produce an improvement: subjects who were offered low monetary rewards produced lower performance than subjects who were not offered any monetary compensation. Their main finding is that performance varies in a non-monotonic way with incentives.

Ariely *et al.* [4] run experiments where there are different types of tasks; some tasks concentrate on motor skills, some on memory and some on creativity. The highest level of monetary reward produced a lower performance in all tasks of the first experiment; in the second experiment the task involved only physical effort and they find lower performance (for higher incentives) in motor skill and creativity, as the psychological literature predicts.

Finally, incentive effects have also been investigated in the context of positional learning. Anderson [2] considers a "no payoff" treatment (where participant are paid a fix amount), "payoff" and "double payoff" treatment where, instead, monetary rewards depend on subjects' decisions. In this respect, she finds that rewarding the correct decision reduces the amount of the decision error, but increasing the payment for a correct decision does not reduce the error over the range of payoffs considered.

3 Theory

This Section is divided in two parts. In Section 3.1 we describe and solve the Chinos Game, characterizing the unique guess sequence compatible with a Perfect Bayesian Equilibrium (PBE hereafter) of the game. The analysis here is made under the behavioral assumption -business as usual in the related literature- that players only aim to maximize their winning probability. In Section 3.2 we introduce distributional concerns in a simplified version of the game, which allows us to convey the main message of our theoretical conjecture: *payoff comparisons across players may yield rational (equilibrium) shading.*

3.1 The Chinos' Game

In Feri *et al.*'s [13] experimental Chinos Game, three players, indexed by $i \in N = \{1, .., 3\}$ privately receive a signal s_i (either 0 or 1) identically and independently drawn from a fixed probability distribution, with $p > \frac{1}{2}$ denoting the probability of $s_i = 1$ ($p = \frac{3}{4}$ in the experiment). Players act in sequence and have to guess the sum of signals, $\psi \equiv s_1+s_2+s_3$. By the time Player i makes her guess $g_i \in G \equiv \{0, ..., 3\}$, she knows her signal (s_i) and the guesses of those who acted before her in the sequence $\{g_1, ..., g_{i-1}\}$. In this case, the sum of signals for k players follows a Binomial distribution $Bin(k, p)$. Let M_k be the mode of such a distribution. While in Feri *et al.*'s [13] all players who guess correctly (i.e. $g_i = \psi$) receive a fixed prize, our only modification of the original protocol consists in

1. introducing a uniform random draw which selects, at each round, one player in the sequence (the SP, indexed by k), with
2. the SP, conditional on guessing right, winning the prize with probability $\alpha_k < 1$, while the other group members' situation remaining unchanged (i.e. $\alpha_{-k} = 1$).

In each round, both the identity of the SP k, together with her current winning probability α_k are communicated to all group members who may condition their guess to this information.

Let $\mathcal{H}_i$ denote the set of player i's information sets with generic element h, with $\mathcal{H}_1 \equiv \{h = s_1\}$, $\mathcal{H}_2 \equiv \{h = (g_1, s_2)\}$ and $\mathcal{H}_3 \equiv \{h = (g_1, g_2, s_3)\}$.

Strategies and beliefs are conventionally defined. A behavioral strategy for Player i is a mapping $\gamma_i : \mathcal{H}_i \to G$, with $\gamma_i^h(g_i)$ is the probability of guessing g_i at information set h. By the same token, a system of beliefs is defined as $\mu_i = \{\ \mu_i^h \in \Delta(h)\}$, with $\mu \equiv (\mu_i)$

If we assume that players aim to maximize their winning probability -as it is common in the literature on positional learning- given the realized vector of signals $s \equiv (s_1, s_2, s_3)$, there exists a unique equilibrium path, common to all the PBE of the game:

$$\begin{aligned} \bar{g}_1(s_1) &= s_1 + M_2, \\ \bar{g}_2(g_1, s_2) &= (g_1 - M_2) + s_2 + M_1, \\ \bar{g}_3(g_2, s_3) &= (g_2 - M_1) + s_3. \end{aligned} \tag{1}$$

To see this, remember that, since p is common knowledge, also M_1 and M_2 are common knowledge. Thus player 2 and Player 3 can infer s_1 from g_1 (*i.e.*, $s_1 = g_1 - M_2$). By the same token, Player 3 can infer s_2 from g_2 since $g_2 - M_1 = s_1 + s_2$. Therefore, in equilibrium, each player perfectly reveals her signal and takes expectations (by way of M_i) over the sum of signals of her successors in the sequence. This is equivalent to say that the higher the player position, the higher her chances to win the prize (i.e. $\Pr(s_2 + s_3 = M_2) = p^2 < \Pr(s_3 = M_1) = p < 1$). Moreover, by (1), Player 3 needs not look at Player 1's guess to evaluate her optimal behavior, since all relevant information regarding s_2 *and* s_1 are contained in g_2. Since our experimental conditions imply $p = \frac{3}{4}$, the corresponding PBE path can be derived by substituting $M_1 = 1$ and $M_2 = 2$ in the expressions above. Notice that this result is not affected by the introduction of our exogenous random shock.

3.2 Signaling in the Chinos Game

In this Section, we provide some formal dress to our working hypothesis: *positional learning gives rise to rational shading if players have distributional preferences.* To show, we further simply matters and consider a toy example in which there is uncertainty only on Player 1's signal (i.e. it is as if we were assuming that Player 2's probability of winning only depends on her ability to properly decode Player 1's guess, g_1). In case of a correct guess, Player 1's prize is smaller, this indicating the feature of the Chinos game by which, in equilibrium, Player 1's probability of winning is smaller than Player 2's. Figure 3 draws the game-form associated to the strategic situation we just outlined.

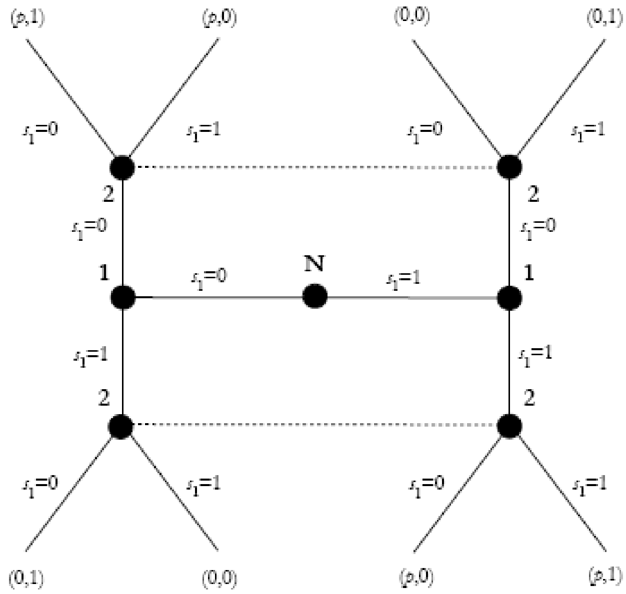

Fig. 3. A simplified version of the Chinos Game of Fig. 1

Let $\sigma_1^k = \gamma_1^h(1)$ ($\sigma_2^k = \gamma_2^h(1)$) denote the probability with which Player 1 (2) delivers the guess $g_1 = 1$ ($g_2 = 1$), after observing Nature's move $s_1 = k$ (Player 1's guess $g_1 = k$). Let also $\mu^k = \Pr[s_1 = 1 \,| g_1 = k]$ be Player 2's conditional probability of a positive signal given g_1, evaluated using Bayes' rule (wherever possible).

Let also $\pi_j^h(\sigma \,|\mu)$ player j's expected monetary payoff evaluated at h, conditional on a given behavioral strategy profile $\sigma \equiv (\sigma_1, \sigma_2)$, with $\sigma_i \equiv (\sigma_i^0, \sigma_i^1)$, and belief system, μ. Since player 2 has no chance of affecting Player 1's probability of winning with her decision, we shall simply assume that Player 2's payoff in the game is perfectly aligned with her expected monetary prize, i.e. $u_2^h(\cdot) = \pi_2^h(\cdot)$. By contrast, as for Player 1's payoff, we consider the following

Assumption 1

$$u_1^h(\sigma) = (1 + \theta_1)\pi_1^h(\cdot) - \theta_1 \pi_2^h(\cdot), \theta_1 > -1. \tag{2}$$

By (2), Player 1's preferences do not only depend upon her own probability of success, but also on the difference $\pi_2^h(\sigma) - \pi_1^h(\sigma)$, where $\theta_1 > 0$ ($\theta_1 < 0$) indicates spiteful (altruistic) preferences.[4] We are interested in characterizing the set of PBE of the game

[4]Notice that, given distributional concerns, player 1's payoffs also depends upon player 2's beliefs, since 1 has to form expectations over 2's response, since from the latter depends player 2's expected monetary payoff which, by (2), affects player 1's evaluations, too. In this Section, as well as in our estimation excercise, our manipulation of beliefs as derived by the observation of public guesses avoids of the complication of modeling higher order beliefs (see the Appendix for the details).

of Figure 3, as a function of the distributional preference parameter, θ_1.[5]

Proposition 1

1. If $\theta_1 < \frac{p}{1-p}$, the game has a unique (truthfully revealing) separating PBE in which $\sigma_1^1 = 1 - \sigma_1^0 = 1$.

2. If $\theta_1 = \frac{p}{1-p}$, the game has

   (a) an hybrid PBE in which $\sigma_1^1 = 1, \sigma_1^0 < \frac{1-p}{p},, \sigma_2^0 = 0$ and $\sigma_2^1 = 1$. and

   (b) another hybrid PBE in which $\sigma_1^0 = 0, \sigma_1^1 > 2 - \frac{1}{p}, \sigma_2^0 = 0$ and $\sigma_2^1 = 1$

3. If $\theta_1 > \frac{p}{1-p}$, the game has a pooling PBE in which $\sigma_1^0 = \sigma_1^1 = 1, \mu^0 = \frac{1}{2}$ and $\sigma_2^0 \in \left[\theta_1(1-p) - p, \frac{\theta_1(1-p)}{\theta_1(1-p)+\theta_1 p^2}\right]$.

Proof.

1. Full revelation implies $\sigma_2 = (0, 1)$, which in turn implies $u_1(\sigma) = (1 + \theta_1)p - \theta_1 > 0 \Longleftrightarrow \theta_1 > \frac{p}{1-p}$.

2a. $\sigma_2^1 = 1$ only if $\mu^1 = \frac{p\sigma_1^1}{p\sigma_1^1 + (1-p)\sigma_1^0} > \frac{1}{2}$, which, in turn, implies $\sigma_1^0 < \frac{1-p}{p}$. Since $\sigma_1 =$ (0,1), $\mu^0 = 0$, which, in turn, implies $\sigma_2^0 = 0$. If $\sigma_2 = (0, 1)$, given $\theta_1 = \frac{p}{1-p}$, $u_1(\sigma_1, \sigma_2) = 0$, for all σ_1.

2b This case is symmetric to 2a. If $\sigma_1^0 = 0$, then $\mu^1 = 1$ (i.e. $\sigma_2^1 = 1$). This, in turn, implies a lower bound on σ_1^1 to make $\sigma_2^0 = 0$.

3 If $\sigma_1 = (1, 1)$, then $\mu^1 = p$ and μ^0 is not defined. This implies that $\sigma_2^1 = 1$. Since $\theta_1 > \frac{p}{1-p}$, a PBE exists iff $\mu^0 = \frac{1}{2}$ and the following conditions hold:

$$\begin{aligned}(1-\sigma_2^0)(p - \theta_1(1-p) + \sigma_2^0(p(1+\theta_1) &< 0; \\ -\theta_1\sigma_2^0 &< p - \theta_1(1-p).\end{aligned}$$

■

Proposition 1 depicts different equilibrium configurations, depending on Player 1's degree of "spitefulness", θ_1. When θ_1 is sufficiently low (or even negative, indicating altruism), the unique PBE implies full revelation, in that it maximizes Player 1's (and hence, Player 2's) probability of winning. As θ_1 grows, shading becomes prominent, up to the extreme situation in which 1 always deliver the most likely guess, $g_1 = 1$, independently on private information. This is because, in this case, the "equitative outcome" in which both players fail (i.e. they both get 0) is sufficiently high in Player 1's ranking, compared with situations in which 1 gets the prize (but Player 2 gets the higher prize, too). Finally, notice that, no matter how high is θ_1, a PBE in which 1 pools at $g_1 = 0$ cannot exist. Last, but not least, as usually happens in signaling games, the

[5]This corresponds to the classic Fehr and Schmidt's [11] model of social preferences when distributional concerns are evaluated by *a single* parameter.

game admits *pooling* equilibria, but not *fooling* equilibria, in which player 1 consistently deliver the wrong message. This partially contradicts the evidence of Section 5.

Proposition 1 covers our experimental Chinos Game, once we extend the model to encompass for 3 players and for a wider variety of guesses. In addition, our utility specification (2) leads naturally to the following:

$$u_1^h(\cdot) = (1+\theta_1^2+\theta_1^3)\alpha_1\pi_1^h(\cdot) - \theta_1\alpha_2\pi_2^h(\cdot) - \theta_1^3\alpha_3\pi_3^h(\cdot); \theta_1^k > -1, k = 2,3; \quad (3)$$

$$u_2^h(\cdot) = (1+\theta_2^3)\alpha_2\pi_2^h(\cdot) - \theta_2^3\alpha_3\pi_3^h(\cdot), \theta_2^3 > -1; \quad (4)$$

$$u_3^h(\cdot) = \alpha_3\pi_3^h(\cdot). \quad (5)$$

4 Experimental design

In what follows, we describe the features of the experiment in detail.

1. *Sessions.* The experiment was conducted in 2 sessions at the Laboratory of Theoretical and Experimental Economics (LaTEx) of the Universidad de Alicante. A total of 48 students (24 per session) was recruited among the undergraduate population of the Universidad de Alicante. The 2 experimental sessions were run in a computer lab. Instructions were read aloud and we let subjects ask about any doubt they may have had.[6]

2. *Matching.* Subjects played anonymously in groups of 3 players for 24 rounds, always with the same opponents, always in the same player position (the latter condition being specific of our design, compared with related papers, such as Anderson and Holt [3], or Alsopp and Hey [1]). Both these features were publicly announced and specifically designed to ease information decoding, letting subjects to tailor their subjective beliefs on their specific player position and on the individual behavior of their own group members. By this design, we were able to collect 16 independent observations of our experimental environment, that is, a comparatively higher number of observations (8x2=16 for 2 sessions of 24 subjects each), compared with related experimental works (4 in [1], 12 in [3]).

3. *Random events.* At each round each player's signal s_i was the outcome of an iid random draw, with $p = \frac{3}{4}$. As we already anticipated, the primary modification of Feri *et al.*'s [13] experimental protocol was to target a player in the sequence with a negative shock by which, in case of a correct guess, she would enjoy the prize only with probability α_k (instead of 1). Within each round $t = 1, ..., 24$, the identity of the SP, k, together with the probability of winning the prize if guessing right, α_k, was randomly determined. Let *time interval* $T_\tau = \{t : 3(\tau - 1) < t \leq 3\tau\}, \tau = 1, ..., 8$, be the subsequence of the $\tau-$th 8 rounds. Within each time interval T_τ, each player was selected once, in a random order, *common to all groups.* This was to synchronize the panel. On the other hand, all other random events (i.e. the realization of $\alpha_k \sim U[0, 1]$ and its actual draw, was iid.

[6]The experiment was programmed and conducted with the software z-Tree (Fischbacher [14]). A copy of the experimental instructions, translated into English, can be found in the Appendix.

4. *Payoffs.* All monetary payoffs in the experiment were expressed in Spanish Pesetas (1 euro is approx. 166 ptas.).[7] All subjects received 1000 ptas. (1 euro is approximately 166 ptas.) just to show up. The fixed prize for each round was equal to 100 ptas. Subjects received, on average, 18 euros for a 45-minute experimental session.

5. *Ex-post information.* After each round, all subjects were informed on all payoff relevant information, that is, the correct guess (and, therefore, their individual payoff) and guesses and signals of all subjects in their group. In addition, the experimental software provided subjects with an *History Table*, to better track the sequence of signals and guesses of all their group members in all previous rounds.

4.1 The Questionnaire

We here briefly summarize the structure of the questionnaire administered to all subjects at the end of the experiment.[8]

1. *Demographics.* The first section of the questionnaire collects information about our subjects' demographics and academic background. In this section we find questions about age, gender (**GEN**=1 for female), weekly budget (**WB,** in euro), and family's wealth (**RoomSizeRatio, RSR,** obtained dividing the family size with the number of rooms of the main residence).

2. *Risk attitudes: Holt and Laury's [20] test.* For all 9 questions, subjects have to identify their preference between two binary lotteries, one of which (Option 1) is characterized by a smaller difference in monetary payoffs (i.e. a smaller variance). The 9 lotteries only differ with respect of the probabilities associated to of the high prize within each lottery: the higher the probability of the high prize, the higher the difference (in favor of the riskier Option 2) in expected payoffs. Following Holt and Laury, we proxy each subject's attitude to risk by the relative frequency of the risky option across all 9 questions (i.e. **HL**$\in [0,1]$, increasing with risk loving).

3. *Cognitive Reflection Test (CRT, Frederick [16]).* The CRT is compound of three simple questions, which are easy in that their solution and easily understood when explained, but to arrive at the right answer candidates need to suppress the first response that springs 'impulsively' to their mind and instead work it out logically. Thus, beyond the basic mathematical skills necessary to answer the three questions, the test is meant measure the ability to overcome impulsive answers. It is also a good indicator of how patient candidates are and how good they are at making decisions. The test yields an index, **CRT**$\in [0,1]$, reporting the relative frequency of correct answers (i.e. higher **CRT** indicates higher cognitive reflection).

[7] It is standard practice, for all experiments run in Alicante, to use Spanish ptas. as experimental currency. The reason for this design choice is twofold. First, it mitigates integer problems, compared with other currencies (USD or Euros, for example). On the other hand, although Spanish pesetas are no longer in use (substituted by the Euro in the year 2000), Spanish people still use Pesetas to express monetary values in their everyday life. In this respect, by using a "real" (as a opposed to an artificial) currency, we avoid the problem of framing the incentive structure of the experiment using a scale (e.g. "Experimental Currency") with no cognitive content.

[8] A copy of the questionnaire, translated into English, can be found in the Appendix.

5 Results

In presenting our experimental results, Section 5.1 first describes our subject pool, using the information derived from the questionnaire. We then provide some descriptive statistics in Section 5.2. Since our model is built upon distributional concerns, and the sequential structure of the game does not admit to affect the predecessors' winning probabilities, we shall only report on Player 1 and Player 2's aggregate and individual behavior. We then estimate in Section 5.3 our structural model (3-4), to test our theoretical conjectures.

5.1 Questionnaire

1. *Demographics.* The questionnaire was completed by all 48 students participating to the experiment. They are aged 18 to 26 (mean 20.04, st. dev. 2.28), 31% of them female. Some two-third of our participants state they are full-time students (i.e. they do not work, even temporally or part time), and most subjects (just above 90%) report that their parents are the main source of income for their family. Average number of people living in the household is 4 (sd .96), while their average weekly budget is 54 euros (sd 72). As for their Academic background, 15% of subjects comes from Economics, 52% from Business Administration, 7.2% from other Social Sciences rather than Economics or Business, while 8% follows Science Degrees.

2. *Risk attitudes and personal traits.* Table 1 reports the correlation coefficients between our questionnaire socio-demographics.

	GEN	**RSR**	**WB**	**HL**	**CRT**
GEN	1				
RSR	.14	1			
WB	-.16	-.13	1		
HL	-.1	.18	.12	1	
CRT	-.4***	.13	.16	-.05	1

Table 1: Correlations between socio-demographics. Standard errors between brackets. ***=1 % significant; **=5 % significant; *=10 % significant.

As Table 1 shows, all correlations but one are not statistically significant, this indicating that our questionnaire explores complementary dimensions of our subjects' heterogeneity. The only noticeable exception is the (negative) correlation between GEN and CRT, indicating a significantly lower cognitive reflection -at least, that proxied by Frederick's [16] test- on female's behalf. This is actually in line with the related literature.[9]

5.2 Descriptive statistics

Table 2 shows the relative frequency with which players' guess coincides with the sum of signals. Table 2 also reports (within brackets) the corresponding theoretical prediction

[9] See Frederick [16], p. 37.

under the assumption that players only aim to maximize their winning probability. Notice that winning frequencies increase with player position, although at a "slower pace" than the profit maximizing benchmark.

Player	Frequency of guessing right
1	.43 (.56)
2	.55 (.75)
3	.59 (1)

Table 2: Winning distributions

Table 3 summarizes Player 1's aggregate behavior. In Table 3*a)* we report behavioral strategies (i.e. guesses conditional to signals), with regular (bold) type indicating absolute (relative) frequencies. In Table 3*b)* relative frequencies are calculated conditional on Player 1's guess (instead of Player 1's signal).

g_1	0	1	2	3
$s_2 = 0$	4	19	57	8
%	**.04**	**.22**	**.65**	**.09**
$s_2 = 1$	8	26	110	152
%	**.03**	**.12**	**.43**	**.42**

a)

g_1	0	1	2	3
$s_2 = 0$	4	19	57	8
%	**.33**	**.32**	**.44**	**.05**
$s_2 = 1$	8	26	110	152
%	**.67**	**.68**	**.56**	**.95**

b)

Table 3: Player 1's aggregate behavior

From Table 3*a)* we first observe that the profit maximizing guess -see (1)- corresponds to the modal choice when $s_1 = 0$, but not when $s_1 = 1$ where -basically, Player 1 mixes between g_1 =2 and g_2 =3 with equal probability. In this respect, average play configuration is reminiscent -up to some noise- of the hybrid PBE 2b, in that Player 1 mixes conditional on the high signal only. Consistently with 2b, if belief formation did follow relative frequencies of use -which is our case, see (11) in the Appendix- Player 2, after observing $g_1 < 3$, should assign to the event $s_1 = 1$ a posterior probability greater that $\frac{1}{2}$. In Table A1 (in the Appendix) we summarize Player 2's aggregate behavior. Here again, willingness to reveal greatly differ across information sets, as we observe a rather different behavioral pattern, depending on player 1's message, g_1. When $g_1 = 3$, player 2's perfectly reveals her signal at least 80% of the times, while, conditional on $g_1 = 2$, player 2 mixes with equal probability between $g_2 = 1$ and $g_2 = 2$ ($g_2 = 2$ and $g_2 = 3$) depending on whether $s_2 = 0$ ($s_2 = 1$).[10]

This evidence, obtained aggregating subjects' behavior observations across matching groups, hides a high heterogeneity in behavior. This is why, in Table A1 (in the Appendix) we report Player 1's behavioral strategies disaggregated across our 16 matching groups (**G1** to **G16**). As Table A1 shows, the various matching groups display great heterogeneity in their conformity with maximization of winning probability, with

[10]Observations for which which $g_1 < 2$ are too few and disperse to draw meaningful conclusions.

i) full conformity obtained only in 2 cases (**G13** and **G16**);

ii) "almost" full conformity (i.e. less than 10% of deviations) in 2 cases (**G2** and **G11**);

iii) "moderate" conformity (10% to 30% of deviations) in other 2 cases (**G9** and **G12**);

iv) pooling "2b type" behavior in 3 cases ((**G3**, **G5** and **G10**);

v) "noisy" behavior (i.e. behavioral patterns which do not follow any of the equilibrium profiles listed in Proposition 1), for all other cases, up to the extreme case of **G4**, which plays a completely mixed behavioral strategu in which about $\frac{1}{2}$ of the times guesses 1 or less.

Player 1 between-subject heterogeneity creates, in turn, great heterogeneity in the entire development of group behavior (as Figure 2 clearly shows). In the next Section, we shall apply our model of distributional preferences to check whether deviation from profit maximizing behavior is consistent with spiteful preferences (and how the latter are sensitive to subjects' socio-demographics).

5.3 Estimating spiteful behavior

We are now in the position to estimate, both at the aggregate level and for each experimental matching group, a behavioral model in which at each point in time $t = 1, ..., 24$, (common) players' beliefs μ_t^h are evaluated by (11). Following (3-5), v_{it}^l is the value associated to option $l = 0, ..., 4$ by player i, with

$$v_{it}^l = u_i^h(e^l \left| \mu_t^h \right.) + \varepsilon_{it}^l, \tag{6}$$

where $e^l = \left[e^l(j) \right]$, with $e^l(j) = 0$ if $j \neq l$ and $e^l(l) = 1$, and ε_{it}^l is independently and normally distributed, with mean 0 and constant variance (to be estimated together with the other parameters of the model). By (6), subject i guesses l at round t if

$$l \in \arg\max \left[\left\{ v_{it}^0, \ldots, v_{it}^3 \right\} \right].$$

Under our assumptions on stochastic term ε_{it}^l, the probability that individual i guesses l at round t follows a logistic distribution,

$$\Pr\left(g_i = l\right) = \frac{\exp\left[\lambda_i v_{it}^l\right]}{\sum\limits_{j=0}^{3} \exp\left[\lambda_i v_{it}^j\right]}, \tag{7}$$

where λ_i measures subject i's precision in maximizing her objective function.[11] We augment our behavioral model to include a precision parameter to keep track more efficiently the information transmission along the sequence.

According with (7), our estimation strategy consists in a two-step procedure by which:

[11]See, for example, Stahl and Wilson [24].

1. in the first step we estimate subjects' beliefs μ_t using (11), while
2. in the second step we estimate -via partial maximum likelihood- the distributional parameter profile θ_i and the precision parameters λ_i which better suits subjects' behavior.

Table 4 reports the pool estimation of (7). The reported estimated standard errors in Table 4 take also into account matching group clustering.

	Coeff.	*Std. err.*	*p − value*	*95% conf. int.*	
λ_1	5.32	.9	0	3.54	7.1
λ_2	4.66	.53	9	3.62	5.7
λ_3	1.33	.24	0	.84	1.82
θ_1^2	.37	.11	.01	.15	.59
θ_1^3	.025	.11	.8	-.17	.22
θ_2^3	.53	.24	.03	.06	1

Table 4: Pool estimates of ()

As Table 4 shows, the estimates of λ_i detect a decay in players' accuracy along the sequence (where the loss in accuracy is particularly noticeable between Player 2 and Player 3). Also the estimates of θ_i^j exhibit a decay in distributional concerns: they are all positive (this indicating the predominance of spiteful motives), but are only significant when they refer to player i's immediate successor. In Table A3 (in the Appendix) we report the estimations of the individual λ_i and θ_i^j for all our 16 matching groups, G1 to G16. Here we find that, at the level of the individual estimation of player 1's parameters, our modely nicely adapts to the taxonomy we produced in the previous paragraph (take, for instance, the extreme cases of **G3**, **G4**, **G5**, **G10**, **G13** and **G16**).

In Table 5 we control our between-subject heterogeneity by conditioning the pool estimates of (7) upon treatment conditions (α_k) and our questionnaire variables (see Section 4.1).[12]

In Table 5, our accuracy parameters λ_i are regressed against socio-demographics and treatment conditions, as follows:

$$\lambda_i = \sum_{j \leq i} \beta_i^j \alpha_j + \beta_{GEN}\mathbf{GEN} + \beta_{RSR}\mathbf{RSR} + \beta_{WB}\mathbf{WB} + \beta_{HL}\mathbf{HL} + \beta_{CRT}\mathbf{CRT}. \tag{8}$$

In (8), α_j, $j \leq i$, are used as regressors. As Table 5 shows, we expect (and find) $\beta_i^j > 0$. As for β_i^i, a positive coefficient indicates that players' accuracy in optimizing their objective function grows with the probability of winning the prize in case of a correct guess (we called it a *direct* effect of α_i on λ_i).This conjecture is in line with many models of bounded rationality, such as McKelvey and Palfrey's [21] QRE), by which the probability of a suboptimal action is decreasing the expected payoff loss. A positive and significant β_i^i is also perfectly compatible with Feri et al's ([13]) model of error cascades.

[12]Also in Table 5, the reported estimated standard errors take also into account group clustering.

	λ_1	λ_2	λ_3	θ_1^2	θ_1^3	θ_2^3
α_1	8.1 (3.7)**	4.01 (1.16)***	.45 (.44)	-	-	-
α_2	-	1.69 (.33)***	.62 (.26)**	-	-	-
α_3	-	-	1.63 (.62)**	-	-	-
$\Delta\alpha_1^2$	-	-	-	.3 (.1)***	-	-
$\Delta\alpha_1^3$	-	-	-	-	.17 (.1)*	-
$\Delta\alpha_2^3$	-	-	-	-	-	.4 (.1)***
GEN	.1 (2.5)	-.6 (1.3)	.33 (.69)	-.5 (.2)***	-.17 (.1)*	-.49 (.3)*
RSR	6.3 (1.3)***	2.05 (1.8)	-.05 (.04)	.01 (.19)	.11 (.09)	.49 (.3)*
WB	-.01 (.03)	-.014 (.4)	.058 (.05)	.01 (.01)	.01 (.01)	-.01 (.01)
HL	5.82 (2.94)**	4.01 (1.1)***	5.45 (2.9)*	-.02 (.33)	-.16 (.3)	-.44 (.77)
CRT	21 (5.25)***	12.3 (6)***	9.48 (3.7)***	-.26 (.32)	-.08 (.22)	.19 (.22)

Table 5: Estimates of λ_i and α_i conditional on socio-demographics. Standard errors between brackets. ***=1 % significant; **=5 % significant; *=10 % significant.

On the other hand, we also expect (and find) β_i^j>0, with $j < i$. This is due to the reduced trust player i holds on j's message, whenever the latter, given $k = j$ (i.e. j is the SP), is -correctly, given our estimates- expected to be noisier than usual (we called this an *indirect* effect). By analogy with our findings in Table 4, we see that also this effect is fading with the distance between player in the sequence (take the case of β_3^1, which is still positive, but not significant). As for the effects of socio-demographics, we find that both CRT and (somewhat more surprisingly) HL have a positive impact on subjects' accuracy.

As for the distributional parameters, $\theta_i^j, j > i$, we opted for the following specification:

$$\theta_i^j = \gamma_i^j \Delta\alpha_i^j + \gamma_{GEN}\mathbf{GEN} + \gamma_{RSR}\mathbf{RSR} + \gamma_{WB}\mathbf{WB} + \gamma_{HL}\mathbf{HL} + \gamma_{CRT}\mathbf{CRT}, \quad (9)$$

with $\Delta\alpha_i^j = \alpha_j - \alpha_i$. In this case, we expect (and find) $\gamma_j > 0$, indicating an increasing spitefulness in the difference in winning probabilities. Again, also this effect fades with the distance between players in the sequence. As for socio-demographics, **GEN** seems to capture the only significant factor, with women, on average, more altruistic than men.

6 Conclusion

This paper provides an alternative -although complementary- explanation to deviation from profit maximizing behavior in the context of positional learning. According to the simple model we develop in Section 3.2, subjects may be willing to consciously reduce their winning probability, if this reduces their comparative disadvantage, in a situation -such as positional learning- where the latter is not due to others' behavior, but simply to the exogenous structure of information transmission (and, in this sense, is not likely to yield reciprocal behavior). Our experimental evidence shows that our additional explanation seems to work better for some experimental groups than others, for which the "error cascade" story seems a more plausible justification to deviation from profit maximizing behavior.

In other words, *subjects' heterogeneity* seems one of key issues when reading the data, even more when we provide a theoretical benchmark which allows for multiple equilibria. In this respect, we shall remind the reader that, in this paper, heterogeneity is dealt in two ways:

1. in Table A3 (in the Appendix), we measure our between subjects heterogeneity by estimating the behavioral parameters of our model (i.e. our between subjects' *heterogeneity*) are estimated -as constant, given the relative small number of observation per subjects (24)- individual by individual, while

2. in Table 5 we condition our (pool) estimates upon the *observed heterogeneity* measured by our questionnaire proxies.

Both approaches have limitations in that *i)* in the individual estimates, we cannot use (against our own evidence) treatment conditions -such as α_k- as explanatory variables in the regressions, while *ii)* in our pool estimates (again, contradicted by our own evidence), we are forced to estimate the behavioral characteristics of a "representative agent", whose estimated parameters greatly differ from those of many of our subjects, if not all.

Two recent papers (namely, Harrison and Rutström [19] and Conte *et al. [10]*) try to solve the above problems by allowing for the possibility that more than one behavioral model may be used to explain the history of the observed choices generated by the same subject (or the same subject pool). To this aim, they employ mixture models to estimate the probability that each of the assumed generating processes applies to the sample, estimating simultaneously-by maximum likelihood- the behavioral parameters associated with each model. While Harrison and Rutström [19] run pooled regressions, and control for heterogeneity using questionnaire socio-demographics, Conte *et al. [10]* consider both within-subjects and between subject heterogeneity, by estimating the distribution over the entire population of the relevant parameters of the model. Although we are working with nested models, as different types are simply characterized by different realizations of the same parameter vectors, a mixture analysis may help us to track better the equilibrium selection problem at the group level (i.e. the convergence of different matching to different equilibria of the game).

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Appendix

7 Feri et al's [13] "error cascades"

To evaluate profit maximizing behavior, we first estimate, at each round t and for each matching group, behavioral strategies $\hat{\gamma}_{it}^{h} = \left\{\hat{\gamma}_{it}^{h}(g_i)\right\}$, $i = 1, 2, 3$, as the relative frequency of use of each possible guess at each information set. For information sets never reached at t, we posit uniform play, i.e., we assign equal probability to each guess in G. All this leads to a full-fledged system of behavioral strategies estimated at the beginning of round t, which are constructed as follows:

$$\hat{\gamma}_{jt}^{h}(g_j) = \begin{cases} \frac{\sum_{\tau=1}^{t-1} \chi_\tau(h \wedge g_j)}{\sum_{\tau=1}^{t-1} \chi_\tau(h)} & \text{if } \sum_{\tau=1}^{t-1} \chi_\tau(h) > 0 \\ \frac{1}{4} & \text{otherwise,} \end{cases} \tag{10}$$

where $\chi_\tau(\Xi) = 1$ if the event Ξ occurs in round τ, and 0 otherwise. In words, to estimate Player j's behavioral strategy at h, Player i simply counts the number of times Player j has guessed g_j at h, conditional on h being visited sometime in the past. Otherwise, we assume that i assigns a uniform probability distribution over j's behavioral strategies at h. Once these (assumed common) perceptions on behavioral strategies $\hat{\gamma}_{it}^{h}$ are derived, we can evaluate the induced conditional probabilities of signals over guesses:

$$\beta_1^{(g_1)} = \begin{cases} \frac{(1-p)\hat{\gamma}_1^0(g_1)}{(1-p)\hat{\gamma}_1^0(g_1)+p\hat{\gamma}_1^1(g_1)} & \text{if } g_1 < 3, \\ \frac{p\hat{\gamma}_1^1(g_1)}{(1-p)\hat{\gamma}_1^0(g_1)+p\hat{\gamma}_1^1(g_1)} & \text{if } g_1 = 3; \end{cases} \tag{11}$$

$$\beta_2^{(g_1,g_2)} = \begin{cases} \frac{p\hat{\gamma}_2^{(g_1,1)}(g_2)}{p\hat{\gamma}_2^{(g_1,1)}(g_2)+(1-p)\hat{\gamma}_2^{(g_1,0)}(g_2)} & \text{if } \begin{cases} g_2 = 3 \text{ or} \\ g_2 = 2,\ g_1 < 3 \text{ and } \beta_1^{(g_1)} > \phi(p) \text{ or} \\ g_2 = 2,\ g_1 = 3 \text{ and } \beta_1^{(g_1)} < 1 - \phi(p) \end{cases} \\ \frac{(1-p)\hat{\gamma}_2^{(g_1,0)}(g_2)}{p\hat{\gamma}_2^{(g_1,1)}(g_2)+(1-p)\hat{\gamma}_2^{(g_1,0)}(g_2)} & \text{otherwise.} \end{cases}$$

with $\phi(x) = \frac{1-2x}{1-3x}$. As explained in Feri et al. [13], these probabilities are identified with the beliefs (as held by other players) that Players 1 and 2 hold the signal that maximizes the probability of winning the prize, conditional on their guesses. For our purposes, these beliefs measure the extent of optimality embodied by the estimated strategies of Players 1 and 2. Given the beliefs $\beta_{1t}^{(g_1)}$ and $\beta_{2t}^{(g_1,g_2)}$ induced by the empirical behavioral strategies computed in (**??**), we are in a position to assess whether the behavior of Players 2 and 3 qualifies as optimal, i.e., maximizes expected payoffs given those beliefs. For each subject (in player position) i, we construct an index variable $br_{it}^{h} \in \{0, 1\}$, which is equal to 1 if and only if Player i selects the optimal guess at the information set h visited at t. Figure 2 tracks the relative frequency $b_{it} = \frac{\sum_{\tau=1}^{t} br_{i\tau}^{h}}{t}$ with which, for each experimental group and up to any round $t = 1, ..., 20$, each Player $i = 1, 2, 3$ submitted her optimal guess (i.e., had $br_{it}^{h} = 1$).

8 Additional statistical evidence

	g_2	**0**	**1**	**2**	**3**
	$s_2 = 0$	0	2	1	0
$g_1 = 0$	%	**0**	**.22**	**.68**	**0**
	$s_2 = 1$	0	2	6	1
	%	**0**	**.22**	**.68**	**.1**
	$s_2 = 0$	1	10	2	0
$g_1 = 1$	%	**.08**	**.77**	**.15**	**0**
	$s_2 = 1$	0	4	21	7
	%	**.02**	**.31**	**.51**	**.16**
	$s_2 = 0$	0	19	24	0
$g_1 = 2$	%	**0**	**.44**	**.56**	**0**
	$s_2 = 1$	0	6	68	50
	%	**0**	**.05**	**.55**	**.4**
	$s_2 = 0$	0	6	40	1
$g_1 = 3$	%	**0**	**.13**	**.85**	**.02**
	$s_2 = 1$	0	5	17	1
	%	**0**	**.04**	**.15**	**.81**

a)

	g_2	**0**	**1**	**2**	**3**
	$s_2 = 0$	0	2	1	0
$g_1 = 0$	%	**-**	**.5**	**.14**	**0**
	$s_2 = 1$	0	2	6	1
	%	**-**	**.5**	**.86**	**1**
	$s_2 = 0$	1	10	2	0
$g_1 = 1$	%	**1**	**.71**	**.09**	**0**
	$s_2 = 1$	0	4	21	7
	%	**0**	**.29**	**.91**	**1**
	$s_2 = 0$	0	19	24	0
$g_1 = 2$	%	-	**.76**	**.26**	**0**
	$s_2 = 1$	0	6	68	50
	%	-	**.24**	**.74**	**1**
	$s_2 = 0$	0	6	40	1
$g_1 = 3$	%	-	**.54**	**.7**	**.01**
	$s_2 = 1$	0	5	17	1
	%	-	**.45**	**.3**	**.99**

b)

Tab. A1. Player 2's aggregate behavioral strategies

s_1	0				1			
g_1	**0**	**1**	**2**	**3**	**0**	**1**	**2**	**3**
G1	0	.4	.6	0	.05	.16	.37	.42
G2	0	0	.83	.17	.06	0	0	.94
G3	0	0	1	0	0	.3	.44	.26
G4	0	.29	.43	.28	0	.06	.65	.29
G5	0	.2	.8	0	0	0	.63	.37
G6	.12	.33	.22	.33	.4	.27	.2	.13
G7	0	.67	.33	0	0	.21	.5	.29
G8	.33	.33	.34	0	0	.17	.67	.16
G9	0	.2	.8	0	0	0	.32	.68
G10	0	0	1	0	0	0	.47	.53
G11	0	.12	.88	0	0	0	.06	.94
G12	0	.17	.67	.16	0	.11	.22	.67
G13	0	0	1	0	0	0	0	1
G14	.2	0	.6	.2	0	.11	.53	.36
G15	0	.67	.33	0	0	.14	.76	.1
G16	0	0	1	0	0	0	0	1
TOT	**.05**	**.22**	**.65**	**.08**	**.03**	**.09**	**.37**	**.51**

Tab. A2. Player 1's behavioral strategies diaggregated for matching groups

	λ_1	λ_2	λ_3	$\boldsymbol{\theta}_1^2$	$\boldsymbol{\theta}_1^3$	$\boldsymbol{\theta}_2^3$
G1	2.49**	7.5***	-.65	-.9	-.69	-.11
G2	12***	3.04***	.12	-.001	.12	.82***
G3	3.67**	5.65***	3.32***	1.12**	.88*	.4
G4	3.03*	3.45***	4.12***	-.16	1.14	.26
G5	9.8***	3.78***	4***	.28*	.6***	.55**
G6	-.47	1.04	.43	-.59	-1.5	-.8
G7	17***	6.4***	1.48***	.92***	.01	-.05
G8	4.7***	6.72***	.86	.97***	.88*	.68***
G9	11***	7.9***	.97**	.44**	-.33	.31*
G10	10.6***	5.01***	.18	.36	.19	-.11
G11	18***	7.76***	1.04**	-.09	-.15	-.23
G12	5.2***	4.5***	1.6***	.24	-.05	.05
G13	∞	6.6***	2.05	-	-	-.02
G14	3.7	3.14***	.84	.26	.22	.35*
G15	5.1***	2.67***	2.31***	.81***	-.32	.74***
G16	∞	7.21***	2.41***	-	-	-.3
TOT	5.32***	4.37***	1.3***	.37***	-.02	.34**

Tab. A3. Structural estimation of (7) by cluster

9 The Experimental instructions

9.1 Welcome to the experiment

This is an experiment to study how people solve decision problems. Our unique goal is to see how people act on average; not what you in particular are doing. That is, we do not expect any particular behavior of you. However, you should take into account that your behavior will affect the amount of money you will earn throughout the experiment. These instructions explain the way the experiment works and the way you should use your computer. Please do not disturb the other participants during the course experiment. If you need any help, please, raise your hand and wait quietly. You will be attended as soon as possible.

9.2 The game

This experimental session consists of 20 rounds in which you and two additional persons in this room will be assigned to a group, that is to say, including you there will be a *total of three people* in the group. You, and each of the other two people, will be asked to make a choice. Your choice (and the choices of the other two people in your group) will determine the amount of money that you will earn after each round. Your group will remain the same during the whole experiment. Therefore, you will be always playing with the same people. During the experiment, your earnings will be accounted in pesetas. At the end of the experiment you will be paid the corresponding amount of Euros that you have accumulated during the experiment.

The game. Notice that you have been assigned a *player number*. Your player number is displayed at the right of your screen. This number represents your player position in a sequence of 3 (Player 1 moves first, Player 2 moves after Player 1 and Player 3 moves after Players 1 and 2). Your position in the sequence will remain the same during the entire experiment. At the beginning of each round, the computer will assign to each person in your group (including yourself) either 0 tokens or 1 token. Within each group, each player is assigned 0 tokens with a probability of 25% and is assigned 1 token with a probability of 75%. The fact that a player is assigned 0 tokens or 1 token is independent of what other players are assigned; that is to say, the above probabilities are applied separately for each player.

At each round, the computer executes again the process of assignment of tokens to each player as specified above. The number of tokens that each player is assigned at any particular round does not depend at all on the assignments that he/she had in other rounds. You will only know the number of tokens that you have been assigned (0 or 1), and you will not know the number of tokens assigned to the other persons in your group. The same rule applies for the other group members (each of them will only know his/her number of tokens).

At each round you will be asked to make a guess over the *total* number of tokens distributed among the tree persons in your group (including yourself) at the current round. The other members of your group will also be asked to make the same guess. The order of the guesses corresponds to the sequence of the players in the group. That is to say: Player 1 makes his/her guess first, then Player 2 makes his/her guess and, finally, Player 3 makes his/her guess. Moreover, you will make your guess knowing the guesses of the players in your group that moved *before* yourself. Therefore, Player 2 will know Player 1's guess and Player 3 will know both Player 1 and Player 2's guesses.

At each round, if you make the correct guess you will win a prize of 100 pesetas and if your guess is not the correct one you will earn nothing.

9.3 The SELECTED PLAYER (el JUGADOR ELEGIDO)

In each round, the computer will select one player in your group at random. We shall call her the SELECTED PLAYER. Her identity will vary from one round to the next, so that, you and the other group members will be selected the same number of time, approximately.

WHAT DOES IT MEAN TO BE SELECTED?

While those players who have not been elected, in case of guessing right, win the prize with certainty, the SELECTED PLAYER win the prize with a certain probability, randomly selected by the computer. This probability, together with the identity of the SELECTED PLAYER, will be communicated to all group members at the beginning of each round.

10 The Questionnaire

As we just anticipated, our questionnaire is divided into four different groups of questions.

10.1 Demographics

1. What is your age?.....years.
2. What is your gender?
3. Which is your university degree?.....
4. How many years have you been studying at the university?
5. What is your relationship with the main source of income in your family?
6. What is the labor position of the person who contributes the main source of income in your family?
7. What was the highest level of education that the main source of income in your family completed?
8. How many people live in your household?
9. How many rooms does the house have you are living in?
10. Did you work during the last week?
11. On average, what is your weekly budget?.....euros
12. What is your health?

10.2 Risk attitudes: Holt and Laury's [20] test

1. Which of these two lotteries do you prefer?
   (a) Winning 2.00$ with probability of 1 in 10 and winning 1.60$ with probability of 9 in 10.
   (b) Winning 3.85$ with probability of 1 in 10 and winning 0.10$ with probability of 9 in 10.

2. Which of these two lotteries do you prefer?
   (a) Winning 2.00$ with probability of 2 in 10 and winning 1.60$ with probability of 8 in 10.
   (b) Winning 3.85$ with probability of 2 in 10 and winning 0.10$ with probability of 8 in 10.

3. Which of these two lotteries do you prefer?
   (a) Winning 2.00$ with probability of 3 in 10 and winning 1.60$ with probability of 7 in 10.
   (b) Winning 3.85$ with probability of 3 in 10 and winning 0.10$ with probability of 7 in 10.

4. Which of these two lotteries do you prefer?
   (a) Winning 2.00$ with probability of 4 in 10 and winning 1.60$ with probability of 6 in 10.
   (b) Winning 3.85$ with probability of 4 in 10 and winning 0.10$ with probability of 6 in 10.

5. Which of these two lotteries do you prefer?
   (a) Winning 2.00$ with probability of 5 in 10 and winning 1.60$ with probability of 5 in 10.
   (b) Winning 3.85$ with probability of 5 in 10 and winning 0.10$ with probability of 5 in 10.

6. Which of these two lotteries do you prefer?
   (a) Winning 2.00$ with probability of 6 in 10 and winning 1.60$ with probability of 4 in 10.
   (b) Winning 3.85$ with probability of 6 in 10 and winning 0.10$ with probability of 4 in 10.

7. Which of these two lotteries do you prefer?

(a) Winning 2.00$ with a probability of 7 in 10 and winning 1.60$ with probability of 3 in 10.

(b) Winning 3.85$ with a probability of 7 in 10 and winning 0.10$ with probability of 3 in 10.

8. Which of these two lotteries do you prefer?

   (a) Winning 2.00$ with probability of 8 in 10 and winning 1.60$ with probability of 2 in 10.

   (b) Winning 3.85$ with probability of 8 in 10 and winning 0.10$ with probability of 2 in 10.

9. Which of these two lotteries do you prefer?

   (a) Winning 2.00$ with probability of 9 in 10 and winning 1.60$ with probability of 1 in 10.

   (b) Winning 3.85$ with probability of 9 in 10 and winning 0.10$ with probability of 1 in 10.

10.3 Frederick's [16] Cognitive Reflection Test

1. A bat and a ball cost € 1.10 in total. The bat costs € 1.00 more than the ball. How many cents does the ball costs?.....cents. (**Answer:** 5).

2. If it takes 5 machines, 5 minutes to make 5 widgets, How many minutes would it take 100 machines to make 100 widgets?.....minutes. (**Answer:** 5).

3. In a lake, there is a patch of lily pads. Every day, the patch double in size. If it takes 48 days for the patch to cover the entire lake, how many days would it take for the patch to cover half of the lake.....days. (**Answer:** 47).